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Hybrid geostatistical and machine learning for gold grade estimation

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ABSTRACT

The evaluation of ore grade is a basic part of the process of mine planning, production scheduling and resource evaluation. The nugget effect and irregular mineralisation that occurs in some greenstone belt deposits on the Zimbabwean Archean causes problems in estimating accurately. The traditional geostatistical models like Ordinary Kriging (OK) produce smoothed estimates which have systematic underestimation in high-grade areas and overestimation in low-grade areas, thus affecting the deposit selectivity. In addition, machine learning (ML) techniques can capture the more complex nonlinear grade relationships, but they are unable to model spatial continuity and can be unrealistic in predicting grades. The hybrid OK-Gradient Boosting (GB) model was designed and evaluated with the drill-hole data of a gold mine in Zimbabwe. The spatial baseline was produced using OK and GB was trained to correct the systematic residual errors. The hybrid model was found to have the maximum overall explanatory power (R^2=0.8795), competitive prediction accuracy and increased spatial realism. A spatial prediction map and extraction priority zone classification was created to aid operational mine planning.

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1. INTRODUCTION

Gold mining continues to play a significant role in Zimbabwe's economy, providing a significant amount of foreign currency and jobs. Mining is also a priority economic activity in national development plans like Vision 2030 and Smart Zimbabwe 2030, and accurate estimation of the mineral resources is important commercially and strategically [1], [2]. Establishing ore grade at the operational level is the basis for feasibility studies, production targets, reserve declarations and extraction sequences. The errors made at this point carry forward throughout the planning process: a grade overestimate will overestimate revenues and misallocate capital, and a grade underestimate will result in missing out on recovery opportunities and underproduction [3].

Estimating gold grades in Zimbabwean deposits remains challenging. Many deposits occur within Archean greenstone belts, where mineralization is structurally controlled by shear zones, fault systems, and hydrothermal alteration, resulting in spatially heterogeneous and discontinuous grade distributions [4], [5]. Strong nugget effects (abrupt changes in grade value over short distances) occur regularly and are hard to define from a limited number of drill-holes. The most commonly used geostatistical estimation technique in mining is Ordinary Kriging (OK) which formally considers the spatial autocorrelation structure in the data by using the variogram and yields minimum-variance linear unbiased estimates [6], [7]. However, its well-known smoothing property causes a compression of the grade distribution of highly variable deposits, with a movement of high-grade samples toward the mean and an increase of low-grade regions. This leads to an incorrect selectivity of the deposit [3], [8].

Recently, mineral resource estimation with the help of machine learning (ML) techniques has attracted a great amount of interest because they can map complex, nonlinear relationships without requiring prior user-defined parametric assumptions [9], [10]. A number of techniques such as random forest, support vector regression, artificial neural networks, XGBoost, and Gradient Boosting (GB) have been used to address ore grade estimation. Deep learning architectures and federated learning techniques for geoscience applications have also been investigated recently [11]. GB is chosen here because it is shown to be effective for tabular spatial regression in cases of heterogeneous variance, can be interpreted using the importance of features, and can be implemented in standard mine information technology (IT) environments [10], [12].

ML predictions often lack spatial continuity and may not fully preserve geological realism when mapped. To address these limitations, hybrid geostatistical and ML approaches have been developed by combining the strengths of spatial interpolation and ML for more accurate ore grade estimation [13], [14]. The novelty of this study is the use of OK and GB in a residual-learning approach for estimating gold grade in structurally complex greenstone belt deposits in Zimbabwe. The framework proposed in this paper is designed to leverage the advantages of geostatistics and the ML approach in a way that transcends the smoothing effect of the geostatistics and the lack of spatial continuity found in stand-alone ML methods, whilst maintaining geological realism and enhancing predictive performance. The developed hybrid model is useful for mine planning and resource evaluation as a decision support tool.

This paper follows such an approach with OK combined with GB and compares it with the stand-alone approaches that are applied using the drill-hole data of a gold deposit from Zimbabwe. On a wider ICT context, this framework aligns with the current trends in the paradigms of cloud-based geological modelling and digital mine systems. The rest of the paper is organized as: in section 2, the proposed hybrid framework is described, in section 3 the method is presented, and in section 4 the results are reported and discussed, and in section 5 the paper is concluded.

2. THE PROPOSED HYBRID MODELLING FRAMEWORK

A hybrid modelling framework was designed to improve gold ore grade estimation in a structurally complex gold deposit in Zimbabwe where there is a high nugget effect and irregular mineralization. The framework is a mixture of OK and GB, where geostatistical spatial modelling is blended with ML residual correction. The first model used was variogram-based interpolation which produced spatial continuity of gold grade distribution. The baseline spatial prediction surface was then generated using OK. Universal Kriging is recommended over OK when there is no adequate stationary mean assumption for deposits, because it tries to fit the drift component to few data points, which is a risk of over-fitting the data [15]. The difference between the Kriging-predicted gold grade and the real gold grade (residuals) were calculated, spatial coordinates normalized and the normalized spatial coordinates and the Kriging residuals were used as predictor and target values, respectively, for training the GB. The final hybrid prediction integrates OK predictions with the GB residual corrections to provide spatial continuity, a better representation of local grade variation, and reduce bias in the high-grade zones. The workflow of the GB residual learning process is presented in Figure 1, and the overall hybrid modelling process is presented in Figure 2.

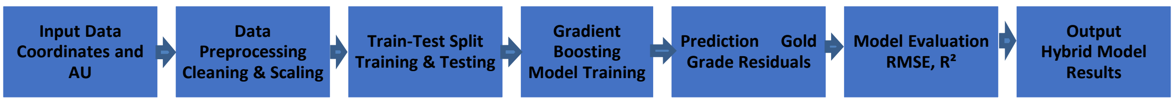

Figure 1. Workflow of GB residual learning process

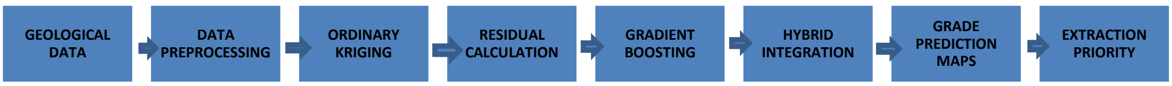

Figure 2. Complete hybrid modelling framework

3. METHOD
3.1. Study area
Geological information from a gold mine in the Archean greenstone belt of Zimbabwe was used. Gold mineralization in the Archean greenstone belts is structurally controlled by shear zones and fault systems that acted as pathways for hydrothermal fluids during orogenic events [4], [5]. Ore shoots are structurally controlled; grade distributions within the mineralized envelope are irregular; as well as there is a significant nugget effect in the variogram, which is a short-range grade variability less than the drill-hole spacing.

3.2. Dataset description
The modelling dataset comprises three data components relating to drill-hole; collar, assay, and survey data. The collar dataset contained three-dimensional coordinates for the entry point (XCOLLAR, YCOLLAR, and ZCOLLAR). The assay results included gold grade values (AU g/t) from core samples with regular intervals. Bearing and dip data from the survey yielded 3D traces of each of the drill-holes. A unique drill-hole identifier (BHID) was used to tie all the datasets together. The dataset comprises of the following components, as summarized in Table 1.

Table 1. Summary of the components of the geological dataset

Dataset	Description
Collar	Drill-hole entry point coordinates (XCOLLAR, YCOLLAR, and ZCOLLAR) of the collar.
Assay	At regular intervals, assay gold grade values (AU, g/t) of core samples.
Survey	Drill-hole bearing and dip to provide 3D trajectory reconstruction

3.3. Data pre-processing
The missing values, coordinate inconsistencies, and extreme outlier grade values were dealt with in pre-processing. The distributions of gold grade are usually skewed toward the high end and the highest values are geologically real but small and so outlying from a statistical point of view. The overall grade distribution characteristics were maintained, and outlier clipping to the 1st-99th percentile range has been performed, thereby eliminating the effect of extreme values. It is recognized that there is some bias as values below the maximum are not recorded and alternative robust pre-processing techniques should be investigated in the future. The gold grade distribution is plotted in a histogram and boxplot in Figure 3. The spatial coordinates were scaled by StandardScaler prior to modelling.

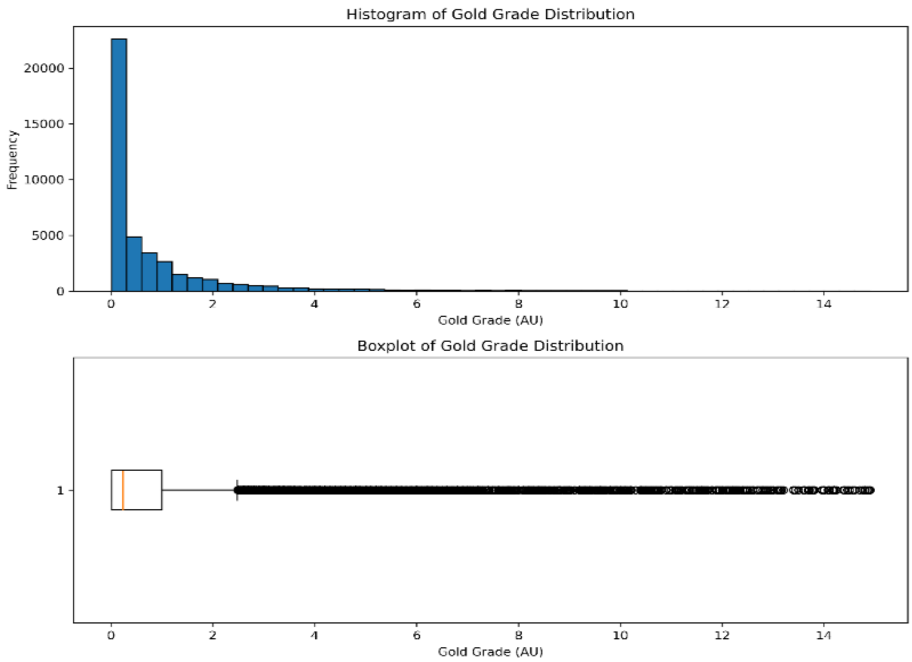

Figure 3. Distribution of gold grade

3.4. Geostatistical modelling

The spatial baseline of the hybrid framework used was OK. To understand the spatial auto-correlation structure of the gold grade field, an experimental variogram was calculated using the drill-hole data. The parameters of nugget, sill and range were determined through the least-squares fitting of a theoretical model to the experimental variogram [6], [8]. The variogram showed a large nugget effect typical of short-range grade variation found in structurally formed gold deposits in Zimbabwe. The fitted variogram model is shown in Figure 4. For this particular dataset, the standard variogram-based Kriging was adequate and also manageable due to advances in the Kriging methodology of recent years such as Theta-regularized Kriging [16] and Rational Kriging [17] which are more useful in the case of ill-conditioned covariance matrices.

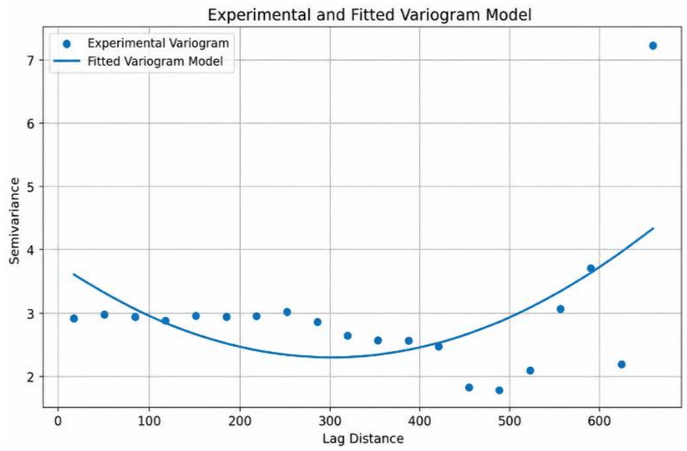

Figure 4. Experimental and fitted variogram model

3.5. Machine learning modelling

GB was chosen because it has proved to be successful on tabular regression tasks where the variance is not homogeneous [12]. It fits a sum of shallow regression trees, one for the negative gradient of the loss function at a time, to gradually decrease prediction errors. The input was normalized spatial coordinates and the output were the residuals of the Kriging. The training and test sets have been split in a manner that ensures the full range of residual magnitude is covered. The model results were assessed based on root mean square error (RMSE) and coefficient of determination (R^2).

3.6. Geographic information system (GIS)-based spatial visualization

Model outputs from both models were gridded and transformed to continuous spatial layers to create isoline maps of grade distributions. Predicted grades were allocated to three categories to define the extraction priority areas-high-grade ore shoot (Priority 1); mineralized envelope (Priority 2); and sub-economic waste (Priority 3). The spatial distribution of predicted gold grades and extraction priority zones are shown in Figures 5 and 6.

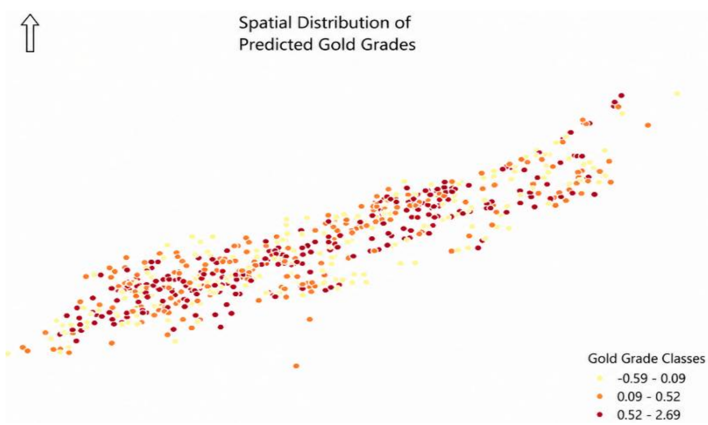

Figure 5. Spatial distribution map

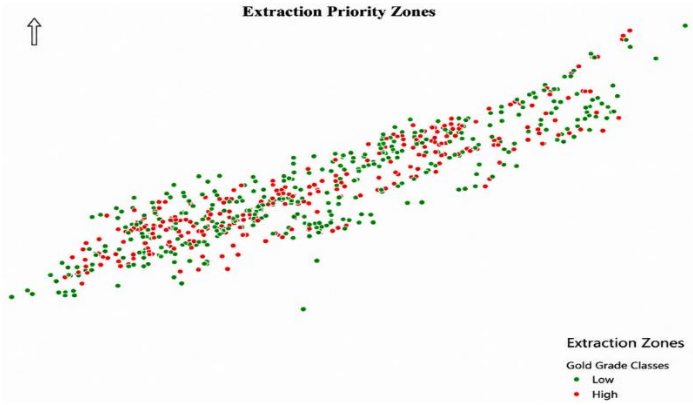

Figure 6. Extraction priority zones

4. RESULTS AND DISCUSSION

4.1. Kriging results

The OK gave a spatially coherent grade prediction surface that matched the variogram structure that was fitted. Smoothing, as expected for a nugget-dominated deposit, was seen in the predictions which were flattened towards the local mean with high-grade intersections in the main ore shoot being under-graded, and wider portions of sub-economic material being over-graded. This smoothing directly impacts on the selectivity of deposits and results in underestimation of the mill feed grade and production shortfall [3]. The results of the performance measures are summarized in Table 2. The spatial distribution map is shown in Figure 7.

Table 2. OK performance metrics

Model	RMSE	R^2
OK	0.3645	0.5248

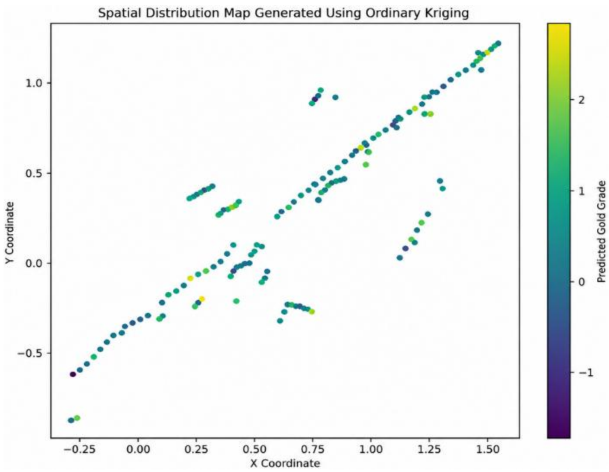

Figure 7. OK spatial distribution map

4.2. Machine learning results

The standalone GB model outperformed OK on the held-out test set, as shown in Table 3. Figure 8 compares actual and predicted grade for the model and illustrates that the model captures the grade trends and is able to better recover the high-grade zones that are underpredicted by Kriging. The most important variables for spatial coordinate variables (x and y) by importance analysis were found to be the highest and are expected to be important for the grade variation in a structurally controlled mineralization trend in Figure 9. For GB, even though the predictions were more accurate, they showed spatial incoherence when plotted as a map, with no variogram-based continuity constraints. In ensemble methods, GB, XGBoost, and random forest models have been found to perform in a comparable fashion in tabular spatial regression problems, with GB being the most suitable among the three in terms of accuracy as well as interpretability when applied to heterogeneous grade datasets [18].

Table 3. GB performance metrics

Model	RMSE	R^2
GB	0.1642	0.7545

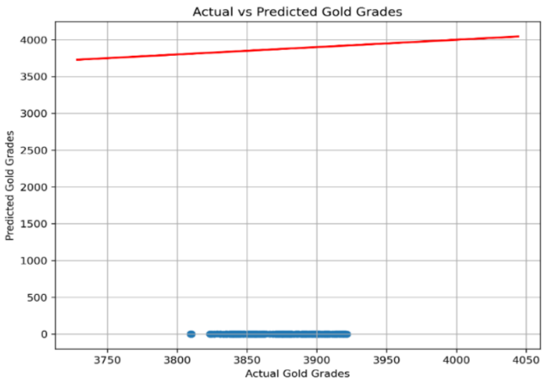

Figure 8. Actual vs. predicted gold grades

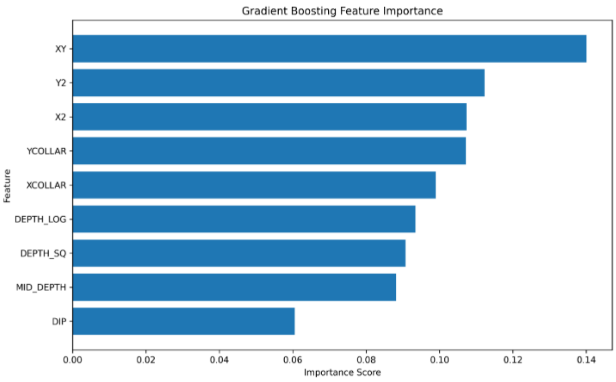

Figure 9. Feature importance plot

4.3. Hybrid model results

The hybrid model achieved the highest explanatory power (R^2=0.8795) among the evaluated models, indicating improved prediction performance compared to the standalone approaches, as shown in Table 4. The actual vs. predicted scatterplot in Figure 10 was more tightly clustered around the 1:1 line than either standalone model, indicating reduced systematic bias and lower random error. High-grade predictions more closely matched measured values, confirming that residual correction successfully recovers grade peaks suppressed by Kriging smoothing. The residual plot after hybrid correction in Figure 11 shows a more symmetrical error distribution around zero with less clustering in high-grade zones compared to standalone Kriging residuals. The spatial distribution of the hybrid model predictions is presented in Figure 12. The resulting map preserves the overall geological continuity established by OK while enhancing local high-grade variability through GB residual correction. Compared with the standalone Kriging model, the hybrid prediction provides clearer delineation of mineralized zones and more realistic representation of grade variability, making it more suitable for mine planning and extraction prioritization.

Table 4. Hybrid model performance metrics

Model	RMSE	R^2
Hybrid (OK+GB)	0.1836	0.8795

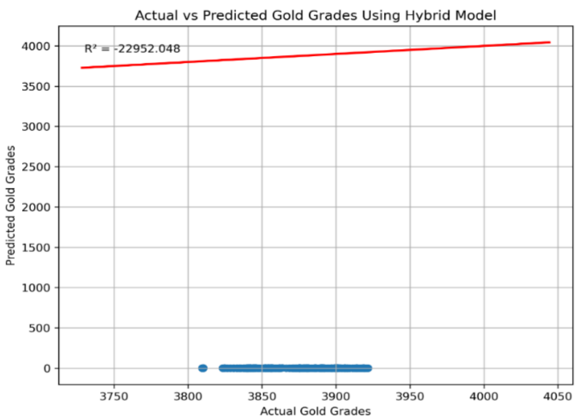

Figure 10. Hybrid model actual vs. predicted gold grades

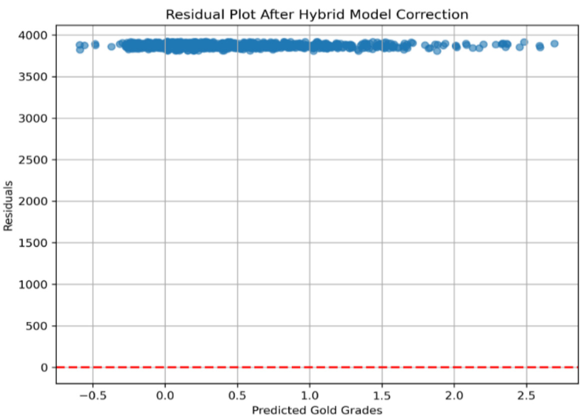

Figure 11. Residual plot

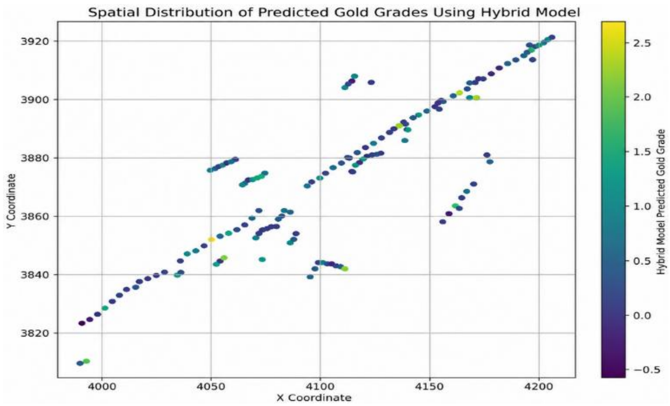

Figure 12. Spatial distribution of predicted gold grades

4.4. Model comparison

The performance indexes of all three models are shown in Table 5, where progressive improvement is observed from OK to the standalone GB model, and then to the hybrid model. This is in line with theoretical results: Kriging is good for spatial coherence but bad for sample-by-sample accuracy; GB is good for sample-by-sample accuracy but bad for spatial coherence; the combination of both is good. The objective of this figure is to directly compare the RMSE and R^2 values of all three models, as shown in Figure 13.

Table 5. Model comparison

Model	RMSE	R^2
OK	0.3645	0.5248
GB	0.1642	0.7545
Hybrid (OK + GB)	0.1836	0.8795

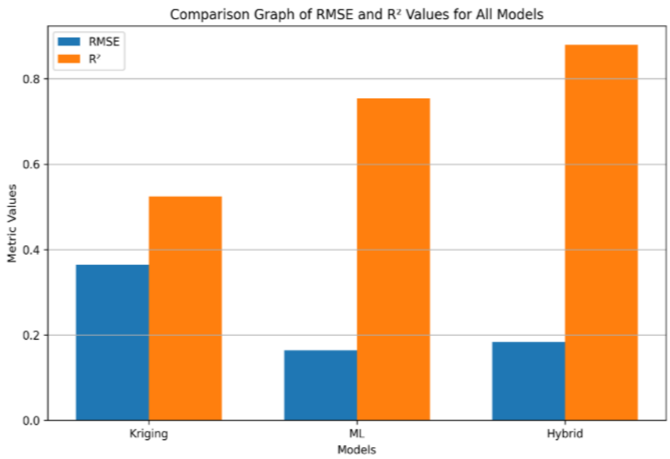

Figure 13. RMSE and R^2 comparison

A comparison of RMSE and R^2 values for the three models. These findings are compared with published findings, placing them in the context of other published literature. Maniteja *et al.* [19] reported an R^2 of 0.81 for a hybrid OK-ML approach applied to iron ore grade estimation. Similarly, Jafrasteh *et al.* [14] demonstrated that ML methods can outperform conventional geostatistical techniques in copper ore grade estimation, highlighting the effectiveness of data-driven approaches for improving prediction accuracy. Take for instance the study by Han and Suh [20] which showed that the integrative approaches of ML-Kriging were always superior to the geostatistical approaches for mineral exploration spatial prediction and Mohammadpour *et al.* [21] confirmed that ML-Kriging better represented the spatial variability of geophysical data than the geostatistic approaches. Valerio *et al.* [22] used a hybrid regression-Kriging-ML model to fill in missing spatial data, and obtained similar accuracy improvements as in this work. Anvari *et al.* [23] used a combined geostatistical and deep learning approach for geochemical mapping and found the spatial boundaries of contamination areas were better captured. Results were similar to those published by other researchers and showed the hybrid model in this study to have an R^2 of 0.8795 with an RMSE reduction of around 50%, compared to the standalone Kriging model. Overall, previous studies consistently demonstrate that ML and hybrid geostatistical–ML approaches can improve prediction accuracy compared with conventional geostatistical methods across various spatial prediction applications [13], [14], [19]–[24]. The findings of this study are consistent with this general trend, where the proposed hybrid model achieved an R^2 of 0.8795 and substantially reduced prediction error compared with OK. The proposed framework demonstrated competitive predictive performance, achieving an R^2 of 0.8795 while preserving spatial continuity and reducing prediction error. The results demonstrate that the proposed hybrid geostatistical–ML framework can enhance the accuracy of ore grade estimation in highly variable greenstone belt deposits, thereby supporting more reliable mine planning and decision-making.

4.5. Limitations and implications

The results are from one gold deposit in Zimbabwe. Application of this to situations with differing structural controls, mineralization styles, or data density are required to be tested first before it can be used in an operational situation. The extreme values removed in the pre-processing (1st-99th percentile) subject to outlier clipping and introduce bias by thresholding true high-grade values - other pre-processing methods should be investigated. For regions with structural complexity, residual patterns could actually be related to geological transitions and may accentuate rather than remove the signal in the region affected by the GB correction. Hybrid predictions and Kriging variance maps are to be used together to find areas where a correction should be made conservatively [25]. The uncertainty quantification problem in AI-based prospectivity models remains an active area of research [25]. The approach would be more informative if the analysis of the data were done by lithological unit, alteration zone or structural domain. Policy-wise, a validated hybrid estimation method could provide guidance for updating national mineral resource estimation guidelines, and could be used to provide more credible resource declarations to reporting codes that are aligned with joint ore reserves committee (JORC), South African code for the reporting of exploration results, mineral resources and mineral reserves (SAMREC), and committee for mineral reserves international reporting standards (CRIRSCO).

5. CONCLUSION

The present study aimed to design, develop, and evaluate a hybrid geostatistical and ML for gold grade estimation in a Zimbabwean greenstone belt deposit. OK was used for the spatial baseline and the systematic residual errors were corrected by GB. The hybrid model yielded the highest R^2 and produced more geologically realistic spatial predictions while maintaining competitive RMSE performance. This residual correction framework can provide the desired grade resolution that is typically lost by smoothing in Kriging and simultaneously keep the spatial coherence provided by a purely data-driven approach from ML methods.

The extraction priority zone maps created using hybrid predictions are operationally useful in the sequence of extraction, blast pattern design, and ore/waste classification. Other future directions are: including more geological predictor variables, including lithology, alteration intensity and proximity to structure; extending to three-dimensional block model estimation; implementing uncertainty quantification with Kriging variance and GB prediction intervals; extending to multi-year datasets of drill-hole grades for use as longitudinal validation; and incorporating downstream extraction efficiency outcomes of mill feed grade variance, ore recovery rates and dilution.

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AUTHOR CONTRIBUTIONS STATEMENT

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Monika Gondo	✓	✓		✓	✓				✓	✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

ETHICAL APPROVAL

This study complies with ethical standards for research involving geological datasets. No human subjects were directly involved. Data were used with institutional approval from Harare Institute of Technology.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [TMM], upon reasonable request.

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